



The impact of knowledge of uncertainty on model calibration

Barry Croke

The Australian National University, Fenner School of Environment and Society, and National Centre for Groundwater Research and Training, Canberra, Australia (barry.croke@anu.edu.au)

Objective functions give a measure of the difference between observed and modelled values, and therefore can be used to both calibrate a model and test the performance under simulation. Uncertainty in observed and modelled values leads to uncertainty in the value obtained using an objective function. Ideally, objective functions should take into consideration the nature of the uncertainties in the observed and modelled values (e.g. variation in the magnitude of the uncertainties, correlation in the uncertainties) with the aim of maximising the signal-to-noise ratio in the derived value.

Most objective functions assume that the uncertainties in the observed and modelled values are homoscedastic (i.e. the uncertainty doesn't vary through the data set). Unfortunately, the assumption is often not valid, and is certainly invalid for hydrological datasets. The result is that the commonly used objective functions (for example, Nash Sutcliffe Efficiency, Root Mean Square Error) are poor measures of a model's performance. Analysis of the impact of heteroscedasticity in the uncertainties using the optimal combinations of observations shows that the significance given to each data point is proportional to the inverse of the uncertainty squared. That is, very high weight is given to the most uncertain data points – independently of whether the uncertainty is known.

There is significant serial correlation in observed and modelled values of streamflow. This is due to the use of rating curves in determining the observed flows, and the memory inherent in the system. Including serial correlation in the uncertainties can further improve the measure of model performance, leading to further reduction in uncertainty in the model predictions. This paper will explore the impact of the knowledge of data uncertainty on model calibration, using synthetic data with known uncertainty. This study only considers the impacts of data uncertainty; uncertainty in how well the adopted model structure represents the actual system is not considered. The results show that perfect knowledge of the uncertainties can lead to significant reduction in predictive uncertainty, while imperfect knowledge can still improve model performance depending on the degree of imperfection.